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Amr Arisha

*Technological University Dublin, [amr.arisha@tudublin.ie](mailto:amr.arisha@tudublin.ie)*

Mohamed Ragab

*Technological University Dublin, [mohamed.af.ragab@gmail.com](mailto:mohamed.af.ragab@gmail.com)*


Wael Rashwan

*Technological University Dublin*

Waleed Abo-Hamad

*Technological University Dublin*

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# Using Modelling and Simulation to Improve Elderly Care in Ireland: A Case Study

Mohamed A.F. Ragab, Wael Rashwan, Waleed Abo-Hamad, and Amr Arisha  
3S Group, College of Business  
Dublin Institute of Technology  
Dublin 2, Ireland

Email: mohamed.ragab@mydit.ie, wael.rashwan@mydit.ie, waleed.abohamad@dit.ie, amr.arisha@dit.ie

**Abstract**—Health care services both globally and domestically - are encountering critical issues due to the increasing demand for services at the time of economic recession. Hospital performance is subject to many constraints, and planning is made more difficult by the complexity and uncertainty of demand. Population ageing is creating immense pressures on healthcare facilities across the world, leaving them struggling to cope with the growing demand for elderly healthcare services. Current demand-supply gaps result in prolonged waiting times for patients and substantial cost burdens for healthcare systems due to delayed discharges. This paper reports on a project that uses modelling and simulation to address elderly care pathways in the Irish healthcare sector. The faster management of frail patients admitted to acute hospitals and the introduction of new intermediate care beds are alternative interventions that healthcare executives are interested in simulating to examine their impact on the performance of the elderly care system. The simulation model developed, along with the statistical analysis, enabled hospital services managers to assess the critical performance and financial issues of the current system, and highlighted the decision variables that could significantly improve the flow of elderly patients.

**Keywords**—Population Ageing, Elderly Care, Discrete Event Simulation, Discharge Planning.

## I. INTRODUCTION

**T**HIS study builds on and extends our previous research presented to the SIMUL 2012 Conference, in Lisbon, Portugal [1]: this extended version includes more detail in all sections.

Advances in pharmaceutical and medical technology during the last century caused a major shift in global demographics, increasing life expectancy to unprecedented figures. So there are now more aged people than ever before - in both developing and developed countries which can be seen as an indicator of advances in global health [2]. Worldwide, there are around 600 million people aged 60 years and over: as Fig. 1-a shows, this total is expected to double by 2025 and to reach virtually two billion by 2050 (World Health Organization - WHO) [3]. In Europe, there are currently 108 million elderly people who constitute 15% of the continent's population, a

figure which is forecast to increase to 26% by 2050 [4], a trend which is reflected in Ireland where the elderly population is projected to grow from 500,000 to 1.3 million over the next 30 years [5]. As Fig. 1-b shows, projections by the Irish National Council on Ageing and Older People (2002) show female and male 'seniors' (65 years and over) accounting, respectively, for 16.4% and 14.1% of the Irish population by 2021[6]. Older people are the major users of health and social care services while elderly patients currently represent 11% of the Irish population, they are estimated to account for up to 50% of hospital bed usage [5]. At the same time as increasing the demand for health and social care services generally, population ageing is affecting the supply of health and social care professionals as the health workforce will have to grow to cope with the demands of the ageing population. These projections constitute a major challenge that is critical to prosperity and quality of life of society as a whole, and promise to put great demand on national healthcare organizations.

Consequently, pressures are now rising on Irish hospitals, not only due to the increased demand for acute hospital beds, but also because elderly patients use hospital resources disproportionately: these demographic changes mean that Irish hospitals are struggling to fill the existing gap between supply and demand while maintaining their service quality[5]. The global economic crisis has inflicted severe cuts on available healthcare funds and led to a 'limited resource' policy in hospitals and other healthcare services: Thus Irish hospitals and elderly healthcare facilities both face equally grave capacity planning challenges if they are to respond effectively to current and projected demand increases [7].

The shortage of beds resulting from this demand increase has had numerous facets that have adversely impacted the overall performance of the Irish healthcare system. Firstly, bed shortages have significantly increased overcrowding in Emergency Departments (EDs), with high percentages of patients leaving without having been seen, and increased mortality rates for elderly patients [5]. Several national reports have highlighted the growing demand for emergency care and the simultaneous decrease in the number of EDs operating to meet this demand; mainly due to economic constraints. Over 1.1 million individuals attended the 33 Irish EDs during 2010, 30% of whom were admitted to hospitals as emergency admissions [8]. Secondly, shortage of community care beds leads to delayed discharges from acute hospitals, which not only delays

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M. Shell is with the Department of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA, 30332 USA e-mail: (see <http://www.michaelshell.org/contact.html>).

J. Doe and J. Doe are with Anonymous University.

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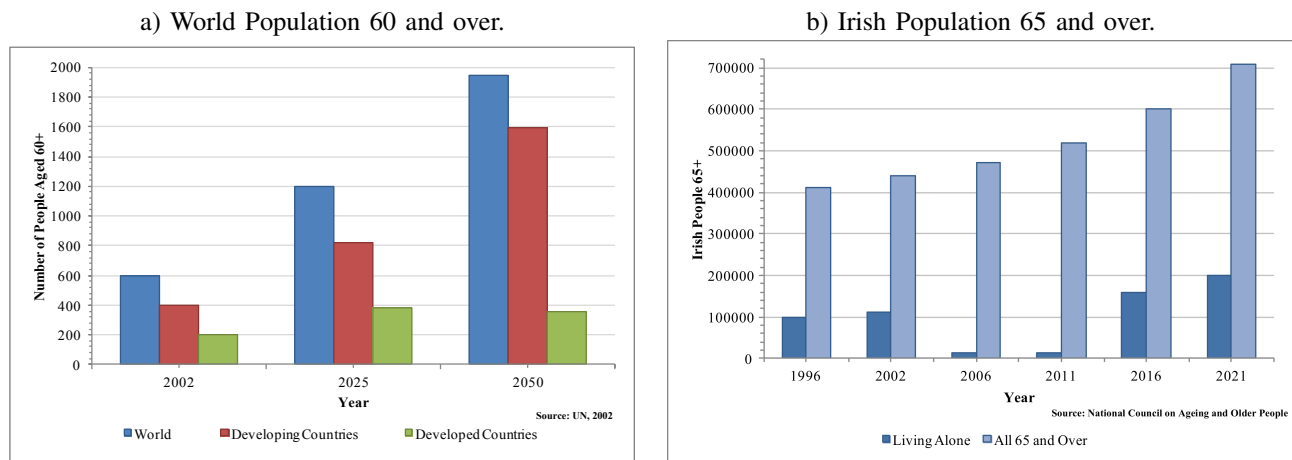


Fig. 1. This figure shows published statistics for the worldwide people aged 60 years and over (sub-figure a) and the Irish population aged 65 and over (sub-figure b).

new admissions to hospitals, but also burdens hospitals with high and unjustified costs, since acute beds are among the most expensive resources of the entire healthcare system [9]. Further complications associated with delayed patient discharges can adversely affect acute hospitals' abilities to cut their waiting lists and deliver their services efficiently and effectively [10]. Finally, delays due to the lack of short- and long-term bed availability create substantial waiting times at many other stages of healthcare systems. As in other sectors, long waiting times in elderly care services are the most frequent source of complaints reported by patients to healthcare executives every year [5]. In Ireland, prolonged waiting times have been reported with more than 500 patients waiting on trolleys for hospital admission every day; 18% of patients are waiting more than 24 hours and 40% between 10 – 24 hours [8]. It is clear that Irish healthcare already operates over capacity, and the overcrowding in EDs can lead to compromises in quality of care and patient safety [11, 12].

This paper presents a project implemented to support Irish health executives in taking decisions about managing the care of elderly patients. By modelling their dispatch pathways, we developed a model that enables those executives to examine the dynamics of their care systems, and also highlights the variability in patients' dispatch delays, and the limitations on the resources available in healthcare facilities. It provides a holistic capacity-planning model that can be used to assess proposed strategies to handle existing bottlenecks and improve the overall experience for elderly patients attending EDs, and throughout the Irish hospital system. The paper begins by reviewing literature on discrete event simulation and its applications in healthcare domains. It then introduces our conceptual model depicting the elderly patients' journeys through the healthcare system and their different discharge destinations. The development phases of the simulation model are then presented, starting with data collection, coding, and then validation. The proposed model is then used to examine two scenarios proposed by healthcare policy makers to improve patient flow, after which experiments and statistical analyses

are conducted to determine the most significant factors that affect patient flows and the magnitudes of their impact. Finally, the paper's findings are reported along with recommendations for future work.

## II. LITERATURE REVIEW

**B**USINESS environments exhibit two types of complexities: combinatorial and dynamic [13]. Combinatorial (or detailed) complexity describes how complex a problem is in terms of alternatives, which may point to the possibility of very large numbers of potential solutions [14, 15] and can be used to represent any combinatorial problem such as scheduling flight legs [16]. In contrast, dynamic complexity relates to non-linear interactions of system components over time, and may appear in even very simple systems [13, 17, 18]. System complexity complicates, and thus can adversely affect, human decision-making processes, which can result in sub-optimal, or even unintended, results (side effects), which are mainly due to the bounded rationality of decision makers [19-21]; misperception and the non-linearity of the complexity [22, 23].

Complexity in healthcare systems stems from various causes, as there are many elements and components involved which interact with and mutually impact each other. Such interactions may be circular, are not easy to capture, so the results of actions and decisions are not immediately obvious or measurable. For example, there will be a delay between when hospital expansion is recognized as being necessary to satisfy increased demand and when the expanded hospital is fully functioning, and there will be time delays and variations between when health problems appear and when actions are taken to restore the system to the desirable state of being able to meet demand. Such non-linear relationships also make it hard to forecast the dynamics of healthcare systems accurately, and complicates decision making processes. For example, the relationship between length of stay (LOS) and admission waiting times is non-linear: if a patient is admitted quickly, it can be expected that his/her medication period will be short - but if he/she has waited for a long time to be admitted, the

medication time is likely to be significantly longer indeed the patient's situation may have worsened considerably while waiting for medication, especially if they are elderly. These make the results of policies intended to improve system's performance may be disappointing, as they may be subject to resistance from staff, in particular consultants, and counter-intuitive behaviour on the part of the policy makers. Simulation and modelling can be an effective and flexible tool to tackle with several of these concerns and so contribute towards improved health system performance and thus better health care provision [25].

In most recent studies of simulation and modelling, discrete event simulation (DES) has been the most widely used in practice. The system's functions are modelled as a finite-state machine in which transitions occur based on events [26, 27]. DES system modelling can be viewed as a queuing network: individual entities (here, patients) go through a process (a consecutive series of activities), each of which may have a queue of other entities waiting to be processed. Individual entities have attributes that reflect their particular characteristics and which determine what happens to them during their journey through the system. The selection of probability distributions is subject to the modeller's decisions, historical data, literatures and the nature of the particular problem being modelled. Traditionally, DES models have been applied to deal with details, process, decision rules, queues and scheduling activities at both operational and tactical levels. Such models require large amounts of quantitative numerical data, and their intrinsic stochastic nature means they need extensive statistical analysis and design experiments. The main target of these models is performance prediction, comparison of scenarios and optimizing performance measurement with accompanying optimization algorithms [28, 29].

Healthcare administrators can benefit from DES to assess current settings and in predicting changes in performance after proposed operational changes. DES models can be very effective tools to deal with hospital problem areas, like operating theatres and emergency departments, where healthcare demand will be variable but resources are likely to be limited [30, 31], and to identify possible areas of improvement that could be achieved via reorganization and re-allocation of existing resources [32, 33]. Many studies have discussed the suitability of DES for modelling healthcare processes in detail [27, 34-37], and they have been used to examine outpatient clinics [38, 39], planning for healthcare services [40, 41]; ambulance scheduling [42]; and improving capacity utilization in intensive care units [43]. A previous study has used a stochastic simulation model for bed occupancy [44], and other applications have included settings - such as emergency departments [25, 45-47], operating theatres [48]; and pre-operative process [49] - in which resources are scarce and patients arrive at irregular times, where modelling can facilitate the effective evaluation and testing of the outcomes of various alternatives and interventions [39]. The dynamic capabilities of simulation can allow a more accurate interpretation of the utilization of hospital resources to be envisaged [50], supporting hospital managers' decisions on bed usage and patient flow through the hospital [51] by modelling problems of patient flows [52], and

then using scenarios to illustrate the consequences of possible solutions suggested by hospital management [53].

### III. PROBLEM CONTEXTUALIZATION

#### A. Background

Elderly patients are usually defined as those who are aged 65 and older and this study adheres to that convention [54]. The most challenging elderly patients are those referred to as frail - as suffering from an array of medical conditions that individually may be curable, but collectively create complex and potentially overwhelming burdens of disease [2]. Frail patients constitute 18 - 20% of the Irish elderly population and usually require longer treatment in the healthcare facilities, followed by rehabilitation and/or community care. In terms of length of stay (LOS), frail patients are characterized in this study as those needing treatment in acute systems (i.e., hospitals) for more than 15 days: The remaining 80 - 82% of elderly patients (who receive shorter treatment periods) are referred to as non-frail. While this study focused initially just on frail patients, since all 65+ patients use the same healthcare system resources, it was found necessary to widen the project's scope to encompass all elderly patients, both frail and non-frail. Although elderly patients utilize a wide range of resources, the initial phase of the proposed model gives special attention to bed capacity in healthcare facilities based on a request from healthcare executives: thus elderly care services that do not involve admissions - such as outpatient clinics - are excluded from the model as they do not affect hospital bed utilization.

#### B. Conceptualization

Elderly patients' journeys through hospital systems usually begin with their arrival at ED by ambulance, walk-in or following a referral by a General Practitioner (GP). After admission, elderly patients receive treatment in acute beds until they are assigned care pathways according to their diagnosis and frailty level. The duration of treatment ranges from few days to two weeks for non-frail patients, but usually exceeds 45 days for frail patients. After their stay in acute beds, elderly patients are discharged to one of the following destinations:

- *Another Hospital:* Certain medical procedures may require equipment that is unavailable in the acute hospital where an elderly patient has been admitted, and they need to be transferred to another hospital where the technology required for the procedure they need is available. Discharge figures to another hospital (6% of all elderly patients) include patients who are moved to undergo certain procedures, and those who are returned to their original hospital after such procedures
- *Rehabilitation:* Patients whose are deemed 'frail', but who are judged as having the potential to improve towards functional independence are discharged to an on- or off-site facility where they receive rehabilitation. Such facilities can be seen as intermediate destinations suitable to the situation where they are no longer categorized as acutely ill, but still need close medical observation in the hope that they will recover [55].

After rehabilitation, the majority of patients (80%) are discharged home, and the remaining 20%, who have not recovered, to long term care.

- *Convalescence*: Around 10% of non-frail patients are discharged to a convalescent care facility for a short stay to recover from a medical procedure. Convalescence offers less intensive care than rehabilitation, as it essentially prepares patients to go home, and may take place within dedicated short stay beds in nursing home facilities.
- *Long Term Care (LTC)*: More than a quarter of frail elderly patients will be unable to live alone at their homes as they are unable to care for themselves, and may require ongoing medical supervision. Such patients are discharged to a public or private nursing home to receive LTC, where they usually stay for years until they die. This prolonged stay in nursing homes hampers the supply of LTC beds in the healthcare system, and can result in waiting times that amount to several months. In addition to hospital demand, there is also a demand from frail patients in the community who need LTC, and must wait in their homes for a nursing home place.
- *Home*: The vast majority of non-frail elderly patients - 88.9% in all - are eventually discharged to their homes, whether directly or after a short stay in convalescence. 24% of frail patients are discharged directly to their homes, and another 28.8% go home after a period of rehabilitation. More than half of them will continue to require medical care in their own homes, and are given Home Care Packages (HCP), which comprise a set of state-provided services that may include home help, nursing, physiotherapy, occupational therapy and other services [5].
- *Other Destinations*: In addition to these destinations, 6% of elderly patients are likely to die during their acute stay, with the probability of mortality increasing proportionally with the frailty level, while another minimal number of patients (slightly more than 1%) with special conditions are discharged to 'other' destinations (e.g., prisons, psychiatric facilities, etc).

Elderly patients' alternative care pathways and their required bed resources are illustrated in Fig. 2, and the percentages of patients discharged to each destination listed in Table I. However, shortages of LTC and HCP bed or service capacities may be the main reasons behind delayed discharges from acute hospitals. Elderly patients can often occupy acute beds for extended LOS, that exceed their treatment periods, not because they continue to require acute health services, but because they are waiting to be discharged [56].

### C. Data Collection

The overall aim of this research is to develop a simulation model to tackle the problem of the delayed discharge of elderly patients in Ireland. Thus this study is a piece of applied research, where the emphasis is on producing relevant practical knowledge. Interviews and observations are qualitative, which is of a great benefit in understanding and modelling work flows

in the healthcare facility. Data quality and precision determines the validity of the simulation model, so the data collection phase represents a critical element of any simulation project. Historical admission and discharge data was collected from the Hospital In-Patient Enquiry Scheme (HIPE), a computer-based system designed to collect demographic, clinical and administrative data on discharges and deaths from acute hospitals nationally, while bed capacities and LOS data were gathered through surveys conducted nationally, and included valuable information about patients and their care journeys, such as arrival times, sources and times of admission and times and destinations of discharge. As in other healthcare modelling projects, collecting the relevant modelling data presented considerable challenges [57]. The first was the dearth of data about certain parameters that were not captured by the HIPE. (It is worth noting that the lack of relevant data caused a similar project studying care of the elderly in the UK to alter its objectives from producing quantitative results to only building a simulation model [55].) The second challenge was that the data was provided in aggregate figures e.g., the numbers of patients discharged to multiple destinations was combined into a single number, while modelling inputs require such figures to be broken down into their individual elements. The third problem with data in this case was inconsistencies between different data sources, such as variations in figures between hospitals data and annual reports. After numerous extended meetings with hospital officials, the absence of certain data and lack of information on how to decompose aggregated figures were overcome by the use of assumptions based on the opinions of experts in the field [58]. Gaining a deeper understanding of what each figure reflected revealed that, in most cases, misunderstandings of terminology or scope were the reasons behind what seemed to be inconsistencies in the data.

Patient information was extricated from the raw data by data manipulation and reorganization, after which data analysis was used to extrapolate important inputs for the model, such as admission and discharge patterns, and to segment frail patient data. The admission pattern of all elderly patients is shown in Fig. 3. Fig. 3-a shows the daily patients admission histogram distribution during 2010. More than 75% of days saw average daily admission rates of between 575 and 675 elderly patients (average 587, standard deviation 88.26). Fig. 3-b presents the monthly demand of patients as a percentage of the total annual demand, which shows the distribution of demand across the months is approximately uniform. Although admission numbers for December are significantly lower than for other months - which may be due to demand decay during the Christmas holidays - demand levels return to normal in January.

While these figures give an overview of the elderly care demand pattern, it would be inaccurate to think all patients present the same demand characteristics: elderly patients' needs and the severity of those needs differ. Accordingly, it was essential to manipulate different admission patterns to reflect the characteristics and needs of different groups of patients. Admission data were clustered to group frail patients into five categories (coded numerically from 0 – 4)

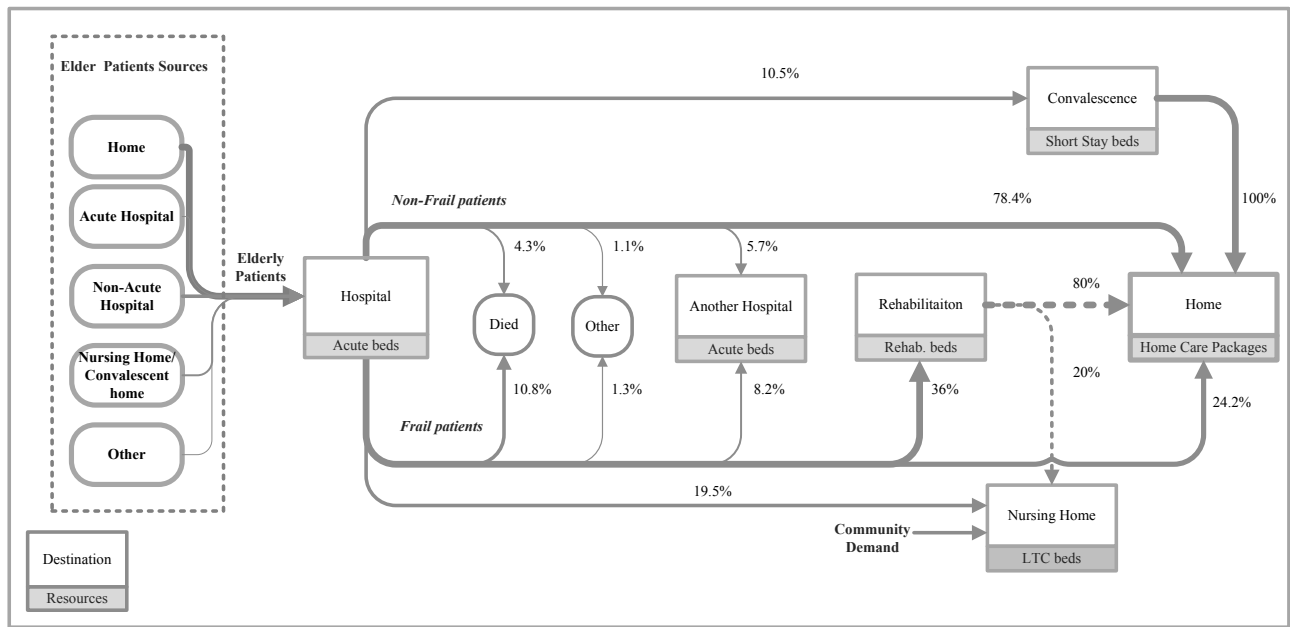


Fig. 2. This figure depicts the Elderly patients care pathways.

TABLE I. DISCHARGE DESTINATIONS PERCENTAGES.

Discharge Destinations	Percentage of Patients		
	Frail	Non-frail	All 65+ Patients
Home	24.2%	78.4%	68.6%
Another Hospital	8.2%	5.7%	6.1%
Rehabilitation	36%	0%	6.5%
Convalescence	0%	10.5%	8.6%
Long Term Care	19.5%	0%	3.5%
Died	10.8%	4.3%	6.1%
Other	1.3%	1.1%	1.1%

according to their acute LOS, which representing the degree of complexity (DOC) of their needs, based on the validated assumption that the most complex cases spend more time in hospital. All 65+ patient data was also categorized into five clusters by age group. Based on the data analysis and this segmentation, elderly patients' degrees of complexity and age groups were used during simulation to define their care pathways through the model. Fig. 4-a shows the percentages of elderly patients classified in each degree of complexity: About 82% are classified as non-frail patients (with zero complexity), the other 18% are classified as frail patients with different degree of complexities. Fig. 4-b shows the different sources of admission categorized by age group. About 90% of all elderly patients came directly from home: as the figure shows, that percentage decreased as patients got more elderly, sloping down from 93% of 65 – 69 year-old patients coming from home to about 84% for the for 85+ age group, which reflects the pattern of their health care demands and emphasizes how elderly people - in particular frail patients - need more care and treatment which they cannot be provided with at home.

#### D. Model Development and Validation

Based on conceptual model development and empirical data analysis, a comprehensive discrete-event simulation model was constructed using a simulation package, with an input/output Excel spreadsheet as a user-friendly interface. Simulation model modules were connected in the same way to the conceptual flow chart, which eased the model construction phase, with, the top level of the simulation model defining the overall model structure, and sub-level blocks comprising additional modules with more details. Object-oriented programming was used to customize pre-defined blocks for constructing the simulation model. The main entities for the simulation were elderly patients, each of which was assigned a set of attributes reflecting a mix of characteristics (such as their degree of complexity and age group) to determine their discharge destination. Statistical assumptions were included by using a Poisson distribution for the admission rate and exponential distributions for service times [56]. These assumptions were validated using the Kolmogorov Smirnov test for goodness of fit with a 95% confidence level. Days were used as the time

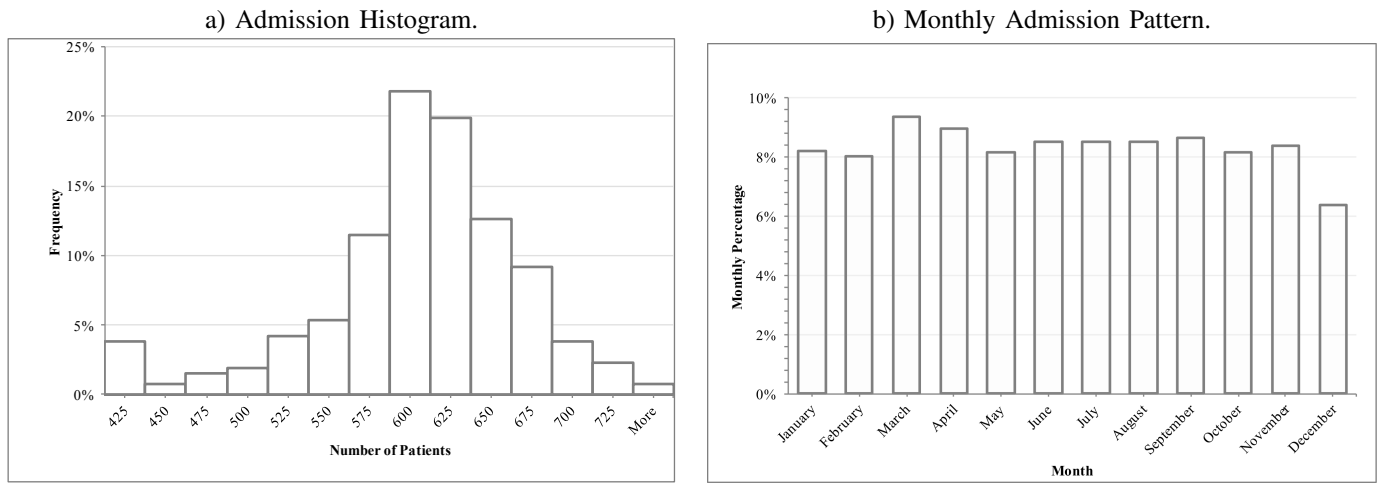


Fig. 3. This figure shows the Admission data of Elderly patients. Sub-figure a presents the admission distribution and sub-figure b shows the monthly admission.

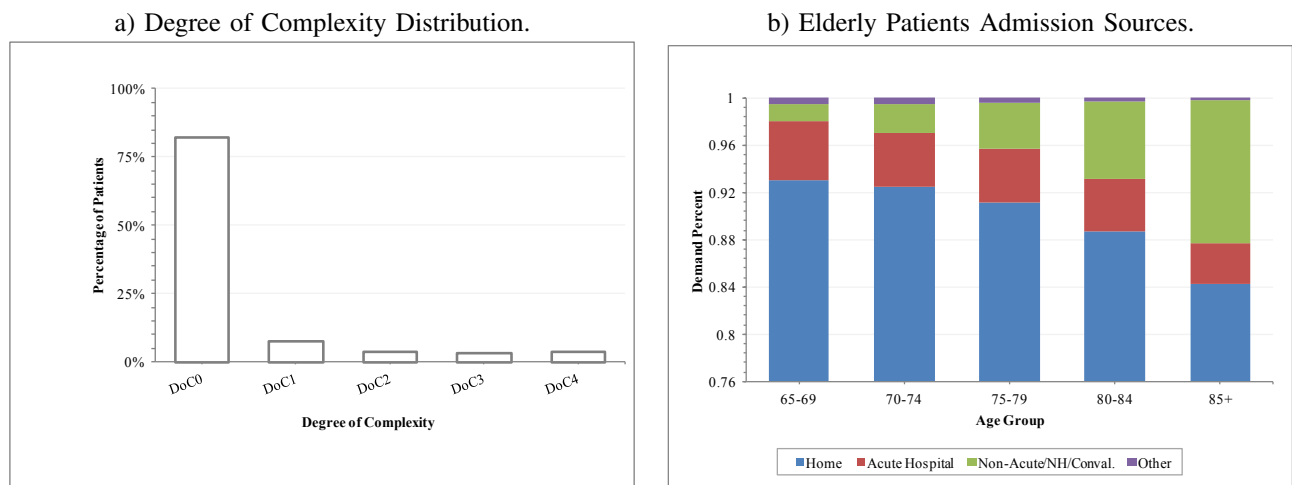


Fig. 4. This figure shows the degree of complexity distribution in sub-figure a and the different sources of admissions and their percentages in sub-figure b.

unit for all modelling inputs and outputs. The measured Key Performance Indicators (KPIs) were saved onto a database after each simulation run, and then exported in tabular form for further analysis and validation.

To reduce the model development cycle time and to increase the confidence in the simulation model's results, verification and validation were carried out throughout the development phase to confirm the model represented actual patient flows [57], and to ensure each model development phase aligned with previously completed phases. The model logic was verified to ensure that patients followed the expected care pathways, by visually tracking patients using animation and by checking intermediate output values such as queue lengths and waiting times. Queues at each patient care stage were initially set as empty and idle, and a three months 'warm-up' period used to mitigate any bias introduced in the simulation model's initial conditions until a steady state was achieved. To compare model results for each scenario with the data provided, we generated results for one year by running the model for 465 days and

discarding the results for the first 100 day warm up period. Different numbers of runs (i.e., replicates) were tested and it was found that 10 runs per scenario were sufficient to obtain unbiased estimators of the expected average of each KPI. The results of the 'as-is' model were validated in two ways. First, stakeholder validation was completed by meeting executives and presenting the simulation model final results to them, and second, the model was validated by comparing simulated figures with the actual figures for patients discharge per age group, per degree of complexity, and per discharge destination (see Fig. 5).

The architecture of the elderly care simulations consists of three main layers (see Fig. 6). Firstly, the simulation model layer, which represents the system structure and logic. The simulation model reflects the interactions between system entities (patients) and different types of resources by creating a network of processes and represents what happens to patients after their admission (patient's pathway). Animated interfaces were provided to the model's users, which are particularly

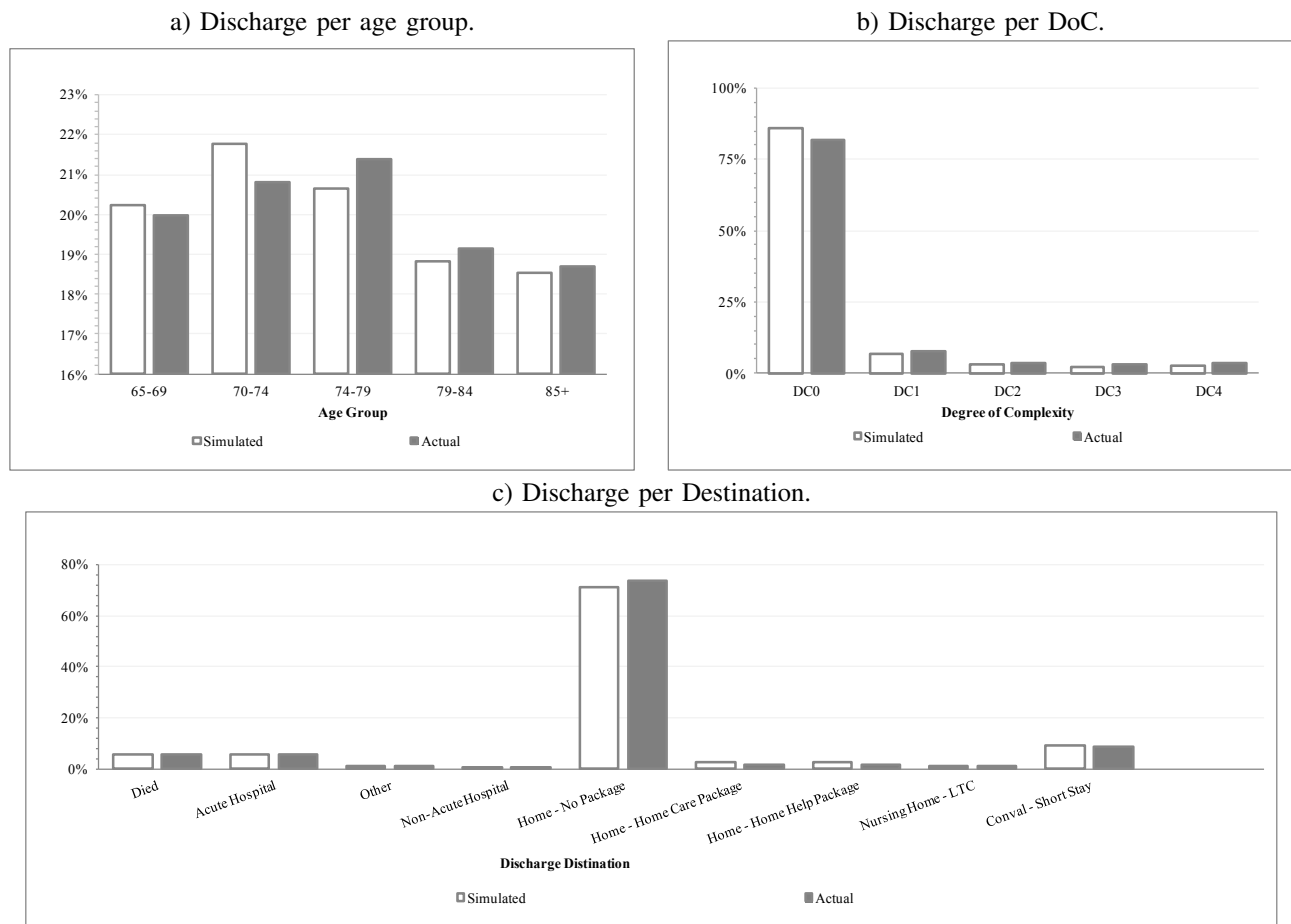


Fig. 5. This figure shows Model Validation; comparing Simulated vs. Actual. Sub-figure a compares the percentage of discharged patients grouped by age for actual and simulated. Sub-figure b compares between simulated and actual percentage of discharged patient in terms of degree of complexity. While sub-figure c compares between actual and simulated discharge destinations.

attractive for end users who need to learn the dynamics of the problem. The second layer is the input output layer, which uses Excel as an external database for input and output variables, to simplify and automate user interaction and policy testing. It enables model users to test different policies related to capacities (i.e., Acute Beds, Rehab Beds, Transitional Beds,...), to see the effects of changes in demand under different scenarios on performance measures, and to quantify the effects of changes in model parameters (i.e., average LOS, Discharge percentages,...) on overall performance. At the start of a simulation run, the model reads input variables from the input data files and stores them in its embedded database in order to speed up the run. At each time step, the simulation model writes the output variables (Queues, resources, and entities related information) to its embedded database, and then to Excel output file for further analysis. After the simulation runs are complete, the Excel output files store huge output datasets which reflect what happened during the simulation. These datasets need to be analysed to generate informative reports to the users (the decision makers), which necessitates a mechanism for displaying the relevant output information.

Excel report generation layer (third layer) is used to analyse the output datasets automatically, and generate summarized reports that include statistical summaries, analysis and figures, so simplifying the output presentation to the end user.

### E. Delayed Discharge

Table II presents the reasons for delays in the discharge of elderly patients, and shows that about half of them were waiting to get rehabilitation beds and the other half for long term care beds. On average about 2,258 elderly patients occupied about 314,711 acute bed days while waiting for rehabilitation care, which represented about 50% of total acute bed days occupied and 17.24% of the total annual acute bed capacity. Their mean waiting time for rehabilitation care was 139 days. Similarly, about 2,720 elderly patients occupied 317,928 extra acute bed days inappropriately (waiting about 118 on average) whilst waiting for long term care (LTC) accommodation. These delays affected both the cost of running health services and patients' wellbeing negatively [10, 59, 60]. Overall, about one-third of the total annual capacity of acute beds was occupied inappropriately by elderly patients, whose need for acute beds



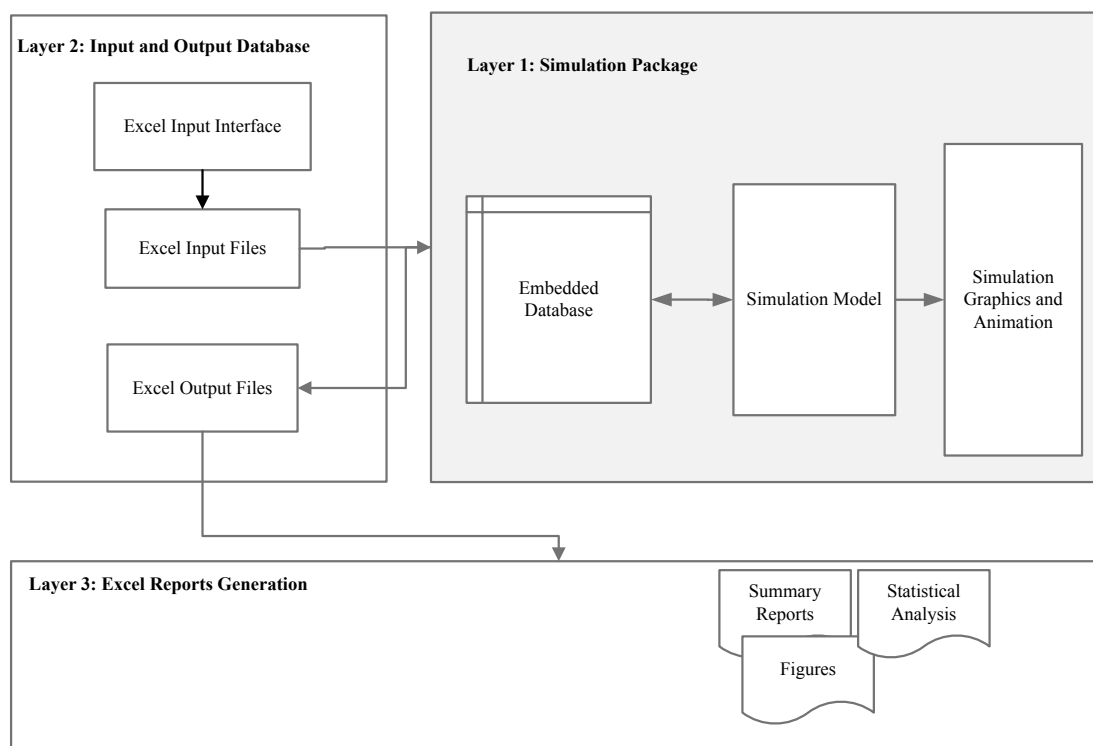


Fig. 6. Elderly simulation model architecture

TABLE II. REASONS OF DELAYED DISCHARGE

Reasons of Delayed Discharge	Average of Patients Waiting	Average Acute Bed Days Consumed / Patient	Total Consumed Acute Bed Nights	% of occupied acute Beds in-appropriately	% of Total Acute Bed Days
Await For Rehabilitation Bed	2, 258	139	314, 711	49.75%	17.24%
Await for Long Term Care (LTC) Bed	2, 720	116	317928	50.25%	17.42%
Total Bed Nights inappropriately Occupied			632, 639.5	100%	
Total Annual Bed Nights Available			1, 825, 000		34.66%

had ended and who were ready to be discharged. This depletion of about one-third of the annual acute bed capacity highlights how delays in discharge is a significant problem for acute hospitals: difficulties in accessing rehabilitation facilities or long term care services were the main factors for these high discharge rate delays.

#### IV. SCENARIOS

**H**OSPITAL executives proposed a number of strategies to the project team to improve patient flow: this section examines these scenarios and considers the key performance metrics involved.

##### A. Key Performance Indicators

Although the model produced a portfolio of results, the following KPIs that focus on acute hospital measures were selected:

- *Acute waiting time:* the average time spent by patients waiting for admission to an acute hospital.

- *Acute access:* the ratio of admitted elderly patients to the overall demand for admission.
- *Average cost per patient:* this cost perspective was added to the model to reflect financial effects of different scenarios. The average cost per patient was calculated by dividing total cost incurred through bed usage by the total number of discharged patients. Due to data confidentiality, the results reported for each scenario in this paper have been anonymized by normalization, i.e., setting the current 'as-is' values at one and reporting scenario results as percentages relative to those figures.
- *Throughput rate:* the total number of elderly patients discharged per year

##### B. Shorter Acute LOS for Frail Patients Scenario

One of the first strategies the management team proposed to improve patient flow was to set a target for how long maximum acute LOS for frail elderly patients - whose current average LOS exceeds 45 days - should stay in acute hospital beds.

Where this length was exceeded, hospitals would be instructed to make earlier decisions about an elderly patient's medical needs and degree of frailty to accelerate their discharge from hospital. A scenario was tested assuming that frail elderly patients would have a maximum acute LOS of 18 days (only slightly longer than the average for non-frail patients).

The results of testing this scenario (presented in the Fig. 7-a) show some improvement in patient flow. Throughput rate and acute access are increased by 6% and 8% respectively, while acute waiting time and cost/patient decrease by similar percentages. It is likely that performance improvements in this scenario would be somewhat limited, since frail patients whose LOS currently exceeds 18 days constitute 54% of all frail patients, but only 10% of the entire elderly population, so reducing this duration would not have a major impact on the efficiency of the system globally. Despite their interest in testing this scenario, healthcare policy makers foresaw its drawbacks. The dependence of acute LOS on patient diagnosis and the medical procedures required could hamper the implementation of a maximum LOS policy, and might face resistance from medical staff. Hence, other more effective and pertinent solutions needed to be sought.

### C. Intermediate Care Scenario

The second strategy proposed was the introduction of a new service similar to the Intermediate Care initiative in the UK that could serve patients who were only using acute or rehabilitation beds for prolonged periods because they were awaiting discharge to LTC [55]. Intermediate care beds would be mostly located offsite in what would be a 'transitional' venue, where frail elderly patients could spend time before being assigned a place in a long term facility. Intermediate Care option can contribute significantly to the efficacy of acute healthcare services by reducing unnecessary acute care admissions and assisting the more timely discharge from acute care beds, which could yield significant cost savings, as the costs of intermediate care beds are estimated to only about half those of acute beds. To assess the impact of this service on the elderly care system, different versions of this scenario were examined using the simulation model developed for this study, with each experiment using different intermediate care beds capacities. These alternatives were based on a gradient increase in intermediate care beds in proportion to a static number of acute beds in the system, starting with 5% of the acute bed capacity and increasing in subsequent versions to 20%.

Introducing intermediate care beds appears to have an overall positive effect on patient flow by noticeably increasing throughput rate and acute access by factors of up to 2.5, while reducing acute waiting times and costs/patient by up to 50% of the current figures (as Fig. 7-b shows). Intermediate care beds can reduce waiting times for both acute and rehabilitation admissions because they accelerate the release of acute and rehabilitation beds back into the system, so more beds are available to meet the incoming demand. Despite the fact that intermediate care would be the last stage that precedes LTC, it is observed that it has almost no effect on LTC waiting time.

This was not unexpected, as LTC waiting time is constrained by LTC bed supply, regardless of where elderly patients are while they await LTC placement.

### D. Design of Experiments and ANOVA

As well as evaluating these two scenarios, healthcare executives were interested in trying to gain insights into the dynamics of the elderly care system, and also to identify the most significant factors affecting its overall performance. Using an orthogonal array ( $L_{27}$ ) a factorial design of experiment was conducted [61, 62]. The Taguchi method uses orthogonal array from the design of experiments theory to study a large number of variables with a small number of experiments. The  $L_{27}$  design allows for testing up to 13 factors at each of three levels: high, medium and low ( $H - M - L$ ). Six selected factors were tested and the values for  $H - M - L$  levels were determined based on the current figures (with one of the three levels set as the 'as-is' value. Twenty-seven experiments were carried out based on the selected orthogonal array, with the system's throughput rate, acute access rate, and acute waiting time as the responses (i.e., outputs) measured in each experiment, as healthcare executives recommended.  $L_{27}$  design for mixed factors was selected and analysed to develop the experimental matrix in Table III. This was followed by a six-way Analysis Of Variance (ANOVA) test to determine the significance of the six selected factors: Number of acute beds, number of rehabilitation beds, number of LTC beds, Acute care average LOS, rehabilitation average LOS, and percentage of rehabilitation patients, using a 5% significance level to test their significance (see Table IV).

The ANOVA results showed that the acute and rehabilitation beds capacities, and percentage of rehabilitation patients were the significant factors that influenced all KPIs based on the  $P$ -value at 5% significance level, while rehabilitation AVLOS influenced both throughput rate and acute access rate, but that neither LTC bed capacity nor acute LOS affected any of the KPIs at 5% significance level. These results illustrate that the acute beds and rehabilitation service represent bottlenecks in healthcare systems that impact on patient flows, and hence negatively affect the whole healthcare process. To determine the relationships between factors and KPIs and their impacts magnitude, multiple regression analysis was applied to the significant factors for each KPI individually.

### E. Regression analysis

Firstly, we traced and investigated all significant factors against the KPIs (responses) to determine if there exist curvature relationships were curvilinear or not, so as to determine the appropriate mathematical transformation, but found all the relationships were linear. So we used multiple linear regression analysis to explore the causality relationships between factors and KPIs, and also tested and validated all the regression model assumptions. Table V presents the summary results of the regression analysis for the three KPIs against their significant factors at 95% confidence level - all three regression models were significant with  $P$ -value  $< 0.00001$  and all individual

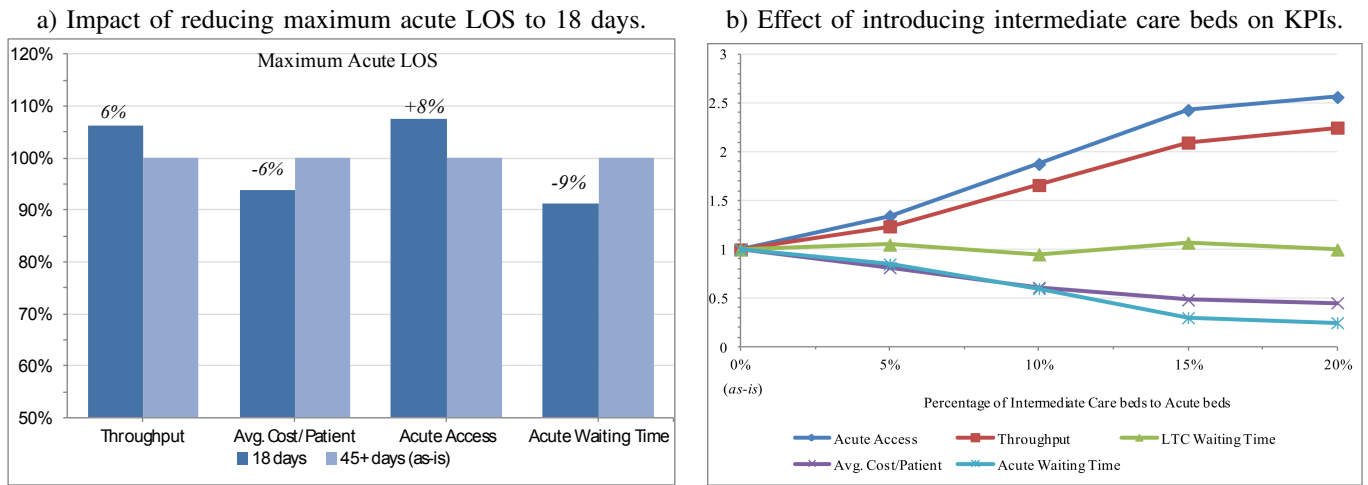


Fig. 7. This figure shows two different scenarios and their impacts on the KPIs.

TABLE III. L27 DESIGN OF EXPERIMENTS.

Experiment	Factors							Key Performance Indicators (Responses)		
	A: NO. Acute Beds	B: No. Rehab Beds	C: No. LTC Beds	D: Acute AVLOS	E: Rehab AVLOS	% Rehab Patients	Acute Access Rate	Throughput Rate	Acute Waiting Time	
1	1	1	1	1	1	1	1	0.958	0.003	
2	1	1	1	1	2	2	0.6	0.587	55.847	
3	1	1	1	1	3	3	0.31	0.314	88.908	
4	1	2	2	2	1	1	0.95	0.939	12.639	
5	1	2	2	2	2	2	0.81	0.803	34.562	
6	1	2	2	2	3	3	0.41	0.421	97.864	
7	1	3	3	3	1	1	0.81	0.827	47.413	
8	1	3	3	3	2	2	0.81	0.813	40.18	
9	1	3	3	3	3	3	0.58	0.61	91.327	
10	2	1	2	3	1	2	0.98	0.951	3.647	
11	2	1	2	3	2	3	0.51	0.509	49.016	
12	2	1	2	3	3	1	0.86	0.837	14.141	
13	2	2	3	1	1	2	1	0.977	0	
14	2	2	3	1	2	3	0.78	0.763	24.614	
15	2	2	3	1	3	1	1	0.968	0.007	
16	2	3	1	2	1	2	1	0.959	0.009	
17	2	3	1	2	2	3	0.94	0.901	8.351	
18	2	3	1	2	3	1	1	0.953	0.025	
19	3	1	3	2	1	3	0.98	0.948	0.457	
20	3	1	3	2	2	1	1	0.968	0	
21	3	1	3	2	3	2	0.8	0.774	12.895	
22	3	2	1	3	1	3	1	0.957	0	
23	3	2	1	3	2	1	1	0.955	0.001	
24	3	2	1	3	3	2	0.89	0.848	8.243	
25	3	3	2	1	1	3	1	0.968	0	
26	3	3	2	1	2	1	1	0.967	0	
27	3	3	2	1	3	2	1	0.954	0.002	

factors were also significant, confirming the ANOVA results. The regression models were then investigated explicitly for

assumptions of homoscedasticity, independence, linearity, and normality. The residuals - the residuals between actual and

TABLE IV. ANOVA SUMMARY RESULTS

Factors	Key Performance Indicators		
	Throughput Rate	Acute Waiting	Acute Access Rate
	P-value	P-value	P-value
<b>A: Acute Beds</b>	<b>0.000064</b>	<b>0.000001</b>	<b>0.000033</b>
B: Rehabilitation Beds	<b>0.014600</b>	<b>0.000002</b>	<b>0.024900</b>
C: LTC Beds	0.604700	0.596000	0.965000
D: Acute AVLOS	0.726700	0.423500	0.590300
E: Rehabilitation AVLOS	<b>0.000300</b>	0.2304001	<b>0.000500</b>
F: % of Rehabilitation Patients	<b>0.000100</b>	<b>0.001500</b>	<b>0.000200</b>
Significance Level $\alpha = 5\%$			

TABLE V. REGRESSION ANALYSIS RESULTS

Factors	KPIs								
	Throughput Rate			Average Acute Waiting Time			Acute Access Rate		
	Coefficient	P-value	VIF	Coefficient	P-value	VIF	Coefficient	P-value	VIF
Constant	0.7801	0.000		30.5192	0.0857		0.7716	0.000	
A: Acute Beds	0.000046	0.000	1.0	-0.0094	0.000	1.0	0.0000531	0.00	1.0
B: Rehabilitation	0.00013	0.01	1.0	-	-	-	0.0001	0.019	1.0
E: Rehabilitation AVLOS	-0.00334	0.000	1.0	0.41616	0.0029	1.0	-0.035	0.000	1.0
F: % of Rehabilitation Patients	-0.728	0.000	1.0	104.8641	0.0008	1.0	-0.775	0.000	1.0
Model-Significance	P-value < 0.00001			P-value < 0.00001			P-value < 0.00001		
$R^2$	78.8%			72.4%			78.3%		
$R^2$ (Adjusted)	74.6%			68.8%			74.3%		
Significance Level $\alpha = 5\%$									

fitted values -, were used to test model assumptions, and any outliers investigated and tested using Cook's distance statistics.

#### F. Discussion

The regression analysis for throughput rate revealed that acute and rehabilitation bed capacities positively affected the throughput rate, while rehabilitation average LOS and percentage of rehabilitation patients were inversely proportionate to the throughput rate. Thus, increasing numbers of either type of bed improved the throughput rate: increasing acute capacity directly increased numbers of patients who could be admitted, provided beds were available at the discharge destinations and the provision of more rehabilitation beds increased the rate of discharge from acute care beds, again improving the throughput rate. On the other hand, increasing average LOS on the rehabilitation care service reduced admissions to rehabilitation care, and thus the discharge rate from rehabilitation care, so negatively affecting the throughput rate. Also, increasing percentage of patients discharged from acute care to rehabilitation increased demand on the rehabilitation service, which could increase its waiting lists, so reducing the rate of discharge from - and thus the rate of admission to - acute care, again, eventually, reducing the whole systems throughput rate. These significant factors explained 78.8% of the system's throughput variations: Fig. 8-a reveals their effects.

The regression analysis for acute waiting times showed that

72.4% of its variations can be explained by acute bed capacity, rehabilitation average LOS, and percentage of rehabilitation patients. Normally, acute waiting times decrease as the acute bed capacity increases - this relationship is clearly straightforward. The provision of acute care beds increases acute care admission rates, reducing waiting lists and waiting times. Conversely, average waiting times for acute care admission are directly proportionate to both rehabilitation average LOS and percentage of rehabilitation patients. But increasing rehabilitation average LOS hinders the acceptance of new patients who are discharged from acute beds for rehabilitation care - so, the rehabilitation care waiting list increases and those patients stay in hospital consuming acute bed resources, so increasing both the acute bed waiting lists and average times. Likewise, increasing the percentage of acute care patients discharged to rehabilitation care increases rehabilitation waiting lists and times - as rehabilitation beds are limited - directly magnifying acute care average LOS, reducing acute care admission rates and lengthening average acute care waiting times. Fig. 8-b illustrates the effect of these factors on average acute waiting times.

Acute and rehabilitation bed capacities, rehabilitation average LOS and percentage of rehabilitation patients explained about 78.3% of the variation in the acute access rate. The influence of both acute and rehabilitation bed numbers on acute access rates are positive, but the influence of both rehabilitation average LOS and the percentage of rehabilitation patients are

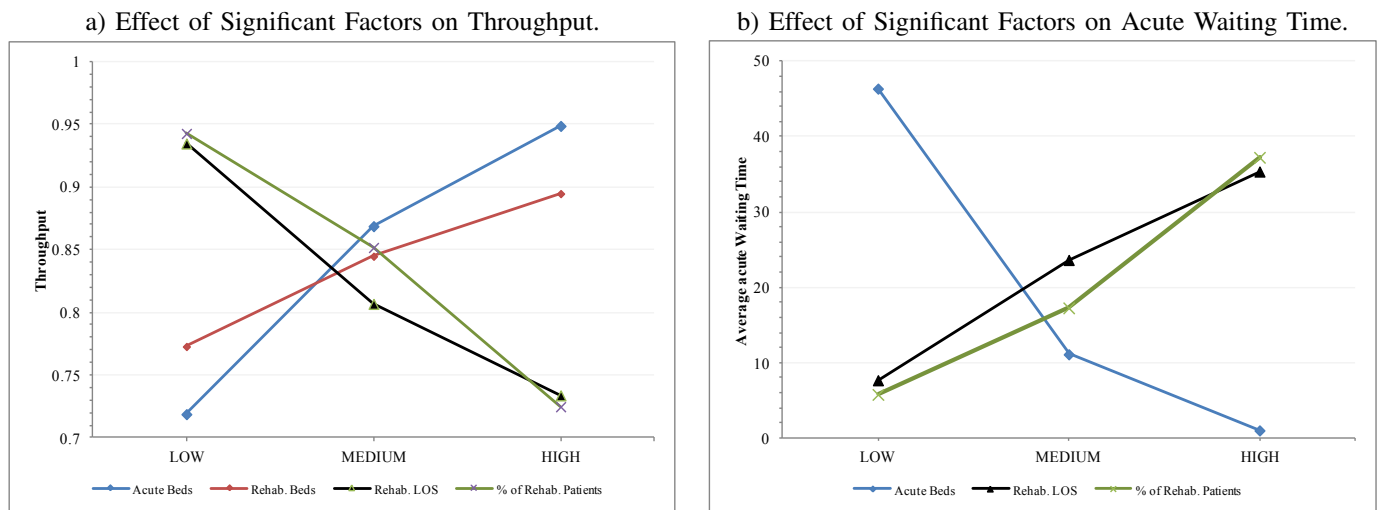


Fig. 8. This figure shows the effect of significant factors on Throughput and Acute Waiting Time.

negative. We found that factors affecting throughput rates were the same as those effecting acute access rates, and that their influences had the same sign. The explanation behind this is that acute access rate is the ratio of admitted elderly patients to the demand for acute care admission thus ratio of acute care out to acute care in in other words, it is a definition of acute care throughput rate. The overall system's throughput rate is positively and highly related to the throughput rates of all its subsystems but, as the acute care subsystem is the core subsystem in an acute hospital (and as many elderly patients encounter it) its throughput rate is likely to significantly determine that of the whole system - and certainly, they are highly and positively correlated.

## V. CONCLUSION AND FUTURE WORK

**T**HE mounting demand for elderly healthcare services driven by increasing population ageing is confronting Irish healthcare executives with critical capacity planning challenges. Developing a simulation model to investigate service constraints in healthcare systems was found to be an approach that was well-suited to provide decision makers with a tool to evaluate their proposed strategies. Conceptual modelling was used to illustrate different elderly patient care pathways and improve understanding of the resources required during their care journeys. This phase was followed by developing a discrete-event simulation model with the object of investigating the impact of demand uncertainty on available capacity, which was of great benefit to policy makers in forecasting the outcomes of potential strategies they wanted to investigate. The reduction of average length of stay of patients using acute beds in hospitals, if possible, only promised minor improvements in patient flows, but results showed that introducing intermediate care beds could enhance the system's performance significantly, reducing delays and the cost of patient stays by almost 50%. The model we developed also had the potential to examine the economic feasibility of implementing this intermediate bed solution fully, based on a cost-benefit analysis,

as well as testing other scenarios the policy makers proposed. An ANOVA statistical analysis revealed that the rehabilitation stage was a bottleneck that affected onward patient flows, so it could be concluded that efforts to improve the flow of elderly patients through the healthcare system should be directed more towards rehabilitation than to other stages of the patient treatment journey, and it is strongly recommended that future research should study the impact of the rehabilitation stage and its capacity on overall patient throughput. Potential strategies that might be considered include setting a maximum rehabilitation LOS and transferring a number of acute beds to rehabilitation.

It is worth emphasizing that the main challenge in this study was the data collection phase. Problems varied between irrelevant or insufficient data and issues of data accuracy, and assumptions made by healthcare experts had to be used to overcome the lack of data in several instances. Comprehensive and periodic collection of elderly patient data is strongly recommended to provide decision makers with a solid foundation to use for process improvement strategies. Another limitation was that a detailed cost analysis was not possible in this study phase due to two main reasons; (1) lack of cost related information and, (2) the high variability of cost models used in Irish public hospitals, which created a high level of complexity. A further problem is that one of this model's limitations is that it assumes demand is static, although this can be overcome by considering it through a dynamic module designed to deal with demographic changes, or via sensitivity analysis. A project recently launched by the same research group will attempt to create a financial model for Irish public hospitals to facilitate cost analysis and optimization

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